# Slow-down or speed-up of inter- and intra-cluster diffusion of controversial knowledge in stubborn communities based on a small world network

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#### Abstract

Diffusion of knowledge is expected to be huge when agents are open minded. The report concerns a more difficult diffusion case when communities are made of stubborn agents. Communities having markedly different opinions are for example the Neocreationist and Intelligent Design Proponents (IDP), on one hand, and the Darwinian Evolution Defenders (DED), on the other hand. The case of knowledge diffusion within such communities is studied here on a network based on an adjacency matrix built from time ordered selected quotations of agents, whence for interand intra-communities. The network is intrinsically directed and not necessarily reciprocal. Thus, the adjacency matrices have complex eigenvalues; the eigenvectors present complex components. A quantification of the slow-down or speed-up effects of information diffusion in such temporal networks, with non-Markovian contact sequences, can be made by comparing the real time dependent (directed) network to its counterpart, the time aggregated (undirected) network, - which has real eigenvalues. In order to do so, small world networks which both contain an odd number of nodes are studied and compared to similar networks with an even number of nodes. It is found that (i) the diffusion of knowledge is more difficult on the largest networks; (ii) the network size influences the slowing-down or speeding-up diffusion process. Interestingly, it is observed that (iii) the diffusion of knowledge is slower in IDP and faster in DED communities. It is suggested that the finding can be "rationalized", if some "scientific

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quality" and "publication habit" is attributed to the agents, as common sense would guess. This finding offers some opening discussion toward tying scientific knowledge to belief.

#### 1 Introduction

Locating, structuring, thereafter simulating stylized facts on the diffusion of knowledge becomes increasingly difficult (see e.g. [1]) due to the huge accumulation of big data. Therefore it is quite needed to downsize the investigations in order to pin point "microscopic phenomena" contributing to the formation of "macroscopic features". This process of looking at the nonlinear dynamics of interacting intelligent populations [2], in socio-physics, is equivalent to the observation of vortices or solitons, in fluid mechanics [3, 4], before attempting to observe and to describe turbulence [5].

It is nowadays commonly accepted that analyzing and modeling real-world phenomena can be made on complex networks [6]. In recent times, interesting observations on the diffusion of knowledge in structuring time dependent networks have followed such a path [7, 8]. In that respect, it was shown how time ordering interactions, thus causality, affect the interpretation of dynamical processes: in particular, by comparing contrasting features on moderate size time aggregated networks and on their sub-structured time dependent counterparts. Authors [7, 8] also showed that some community detection can be made by means of spectral clustering.

Here, a sort of inverse approach is presented. Considering a well defined set of interactions on a network, it will be observed that a difference in the diffusion of knowledge occurs depending on the sub-network size and structure. Numerical results are presented from the comparison of several (small) networks, either when the time ordering of nodes is taken into account or when the network is seen after some time aggregation.

In order to do so, several networks, approximately of the same size, but containing different types of sites and links have been studied. These networks look like small world networks. Moreover, it is imposed that the nodes belong to two communities made of stubborn agents, in order to keep a systematic topological structure, i.e. the diffusion of knowledge is supposed to exist, but without a modification of the state of the recipient, - as when insults are exchanged between agents. Such communities having markedly different opinions have been previously studied in general frameworks [9, 10, 11]. Such communities are, for example, the Neocreationist and Intelligent Design Proponents (IDP), on one hand, and the Darwinian Evolution Defenders (DED), on the other hand [12, 13]. Previous reports on these communities studied along the lines of opinion formation, as well as of behavior choice and agent reactions [14, 15], within a socio-physics context pertaining to the diffusion of ideas have been presented and are very briefly recalled in Sect. 2.

The case of knowledge diffusion within such communities is studied from time ordered selected quotations of agents, whence after building networks, each mimicked by its adjacency matrix, with ranks and rows ordered to define interand intra-community links. These networks are intrinsically directed and not necessarily reciprocal. Thus, the adjacency matrices have complex eigenvalues, and the eigenvectors present complex components [16]. The content of the citations is not studied, but perusal of these indicate that they are more "negative arguments" than "positive ones". However, the diffusion of "knowledge" exists, but without a modification of the state of the recipient, e.g. like when insults are exchanged in many social worlds. There is hardly a search for consensus in such "controversies", indeed.

In Sect. 2.3, the large 77x77 matrix, i.e. a 77 network, is presented. In Sect. 2.4, it is explained that several sub-networks can be extracted for further study: they correspond to small world networks which contain either an *odd* or an *even* number of nodes, in order to pin point the relevance of complex eigenvalues of the pertinent matrix, due to triads of agents. In so doing, it might be possible to observe some possible symmetry (or "transitivity") effects, if any. Thereafter, in Sect. 2.5, the time aggregated (thus, undirected) network counterpart, - which has an adjacency matrix which is symmetric, whence has necessarily only real eigenvalues, is constructed and analyzed.

A quantification of the slow-down or speed-up effects of information diffusion in such temporal networks, with non-Markovian contact sequences, can be made by comparing the real time dependent (directed) network to its counterpart, the time aggregated (undirected) network, - which has real eigenvalues; see Sect. 3 and Sect. 4.

# 2 Perspective on specific stubborn agents

With the aim of capturing the dynamical aspects of the interaction between Neocreationist and Intelligent Design Proponents (IDP) and the Darwinian Evolution Defenders (DED), agents of the IDP and DED groups, the degree of activity of each group and the corresponding degree of impact on the community can be monitored [17, 18]. From a mere opinion formation point of view, it could be shown that if DED would have simply outlined scientific data, i.e., not stating Darwin theory is "proved", but instead noting that it is the best frame to date, they would have lost the debate against the IDP [19, 20].

In order to gain insight on the degree of interrelations due to the activity of such antagonistic social groups [21, 22], a directed network of citations can be constructed, by applying the procedure found in [17] and recalled in Sect. 2.1.

#### 2.1 Network construction

In order to build the network, the main agents of the Intelligent Design (ID) movement were first selected. From a paper by R. T. Pennock [23], criticizing ID, the founders of the ID movement are first identified. Next, the ID web pages and their corresponding links were examined, starting from the URL of the Discovery Institutes Center for Science and Culture (CSC) [24]. Thereafter,

the connexions of this predefined ID community with the defenders of the other community, the Darwins evolution theory defenders are selected. This is helped by considering the increasing impact of the ID movement has impelled. the latter has by reaction activated social and scientific organizations around the world. Among the most important ones, the non-profit organization National Center for Science Education (NCSE) [25] plays a relevant role in coordinating the activity of people defending the teaching of evolutionary biology in the USA.

A citation network has been constructed as follows, in brief searching for nodes (agents of any community citing their own community or the opponents):

- starting from a list containing the name of some of the IDP W. Dembski, M. Behe and S. Meyer, and using Google Scholar Internet search tool, their main publications were selected
- next another list was created with the different authors citing the agents of the previous list, while as objectively as possible recording their general positions upon either one of the two sides of the debate
- a node number was arbitrarily given to each agent
- the node or agent was endowed with an attribute according to the apparent community position
- for each pair of agents a directed link was drawn if, according to the outcome of the Google Scholar search process, there is a citation

N.B. the data was downloaded and examined between Oct. 01 and Nov 15, 2007.

#### 2.2 Network characteristics

The network is composed of two subgraphs, one with 37 and the other with 40 agents, corresponding to IDP and DED communities, respectively. There are 170 and 128 links in IDP and DED intra-communities, respectively, and 217 inter-community links. Notice that no weight is given to any link. One can distinguish between directed links (DL) and undirected links (UL): such a latter link connects a pair of nodes in both directions (A cites B and B cites A); by extension, a Directed Triangle (DT) is the shortest cycle of a graph formed by ONLY directed links (DL) (A cites B cites C cites A, but B does not cite A, etc.). However, the set-up of such adjacency matrices is such that it is impossible to report whether A cited B, before or after C cited B, for example. Moreover, it is also obvious that a DT is a chronologically absurd feature, - except if there are different citations, but this is not recorded in the present procedure. Nevertheless, the adjacency matrices are usually non-symmetric. Thus, systems of unspecified (i.e., directed or undirected) links are at first only those to be considered. One should remind the reader here that the sum of an adjacency matrix and of its transpose, leads to a symmetric matrix with different weights w for directed (w=1) and for undirected (w=2) links

Table 1: Number of nodes, links, and triads, with unspecified (directed or undirected) edges between indicated types of nodes, in the various networks represented by the various adjacency matrices of indicated size

Matrices (Networks)	$M_{77}$	$C_{12}$	$D_{12}$	$M_{24}$	$C_{14}$	$D_{15}$	$M_{29}$	$F_{24}$	$F_{29}$
N.nodes	77	12	12	24	14	15	29	24	29
N.links	307	27	37	125	35	46	152	46	54
	Number of triads								
Triad configuration	$M_{77}$	$C_{12}$	$D_{12}$	$M_{24}$	$C_{14}$	$D_{15}$	$M_{29}$		
IDP-IDP-IDP	21	12	-	12	18	-	18		
IDP-IDP-DED	105	-	-	88	-	-	99		
IDP-DED-DED	171	-	-	129	-	-	165		
DED-DED-DED	51	-	22	22	-	28	28		

Nevertheless, individuals leading the transfer of opinion between IDP and DED communities can be identified by analyzing the number of directed triangles and of undirected links of the citation network. It was found [17] that the three main nodes in the ID community make up for 56% of the IDP triangles and 41% of the inhomogeneous ones, while 5 nodes in the DE community make up for 51% of the inhomogeneous triangles. Thus it can be safely assumed that a few so called opinion leaders can well describe the activity of the whole group to which they belong.

Whence, it should be obvious to the reader that in such small networks, it is hard to get a convincing power law of the degree distributions. However, it seems easily induced that the preferential attachment mode is pertinent for each community, with different "scholarly constraints", as it will be deduced in Sect. 3 and argued upon in Sect. 5.

It is worth calculating the number of triangles associated to each group, i.e. depending on the type of nodes on the triangle edges. The results for the different possible types of triangles are given in Table I. We emphasize that triangles containing elements of different communities are the most abundant ones. Conversely, among the 348 triangles sustaining the network, 72 (thus 0.21 %) are homogeneous, relating only nodes of the same community. Thus, it is obvious that the interactions induce some non trivial dynamics [26, 16], leading to real and complex eigenvalues.

#### 2.3 A 77x77 real asymmetric matrix

The adjacency matrices can be summarized as

$$M_0 \equiv \begin{pmatrix} C_0 & A \\ B & D_0 \end{pmatrix} \equiv \begin{pmatrix} C_0 & 0 \\ 0 & D_0 \end{pmatrix} + \begin{pmatrix} 0 & A \\ B & 0 \end{pmatrix}. \tag{1}$$

in which a matrix element  $m_{ij}$  takes the value 1 or 0 depending on whether or not a citation of i by j has taken place, as recorded and explained in ref. [17, 26]. The matrices  $C_0$  (37x37) and  $D_0$  (40x40) indicate whether agents of

Table 2: Characteristics of the main eigenvalues (EVs) for the various adjacency matrices pertinent to the investigated networks. the cases in which the modulus of an EV (but not the largest one) is larger than the modulus of the second largest real EV is emphasized with an !!

	Matrix								
	$M_{77}$	$C_{12}$	$D_{12}$	$M_{24}$	$C_{14}$	$D_{15}$	$M_{29}$	$F_{24}$	$F_{29}$
N. of Re EVs	14	2	2	4	2	2	4	5	2
N. of c.c. EVs	12	1	3	7	1	3	8	0	2
Largest EV $(\lambda_1)$	7.994	2.588	3.591	6.777	2.588	3.591	6.845	3.661	3.764
$\lambda_2$ if Re EV	2.481	-1.742	1.432	1.553	-1.742	1.432	1.596	0.773	0.662
$ \lambda_2 $	2.481	1.742	1.482 !!	1.827 !!	1.742	1.482 !!	1.760 !!	3.661 !!	3.764 !!
due to			-1.462	-1.577		-1.462	-1.583	-3.661	-3.764
			$\pm i \ 0.240$	$\pm i \ 0.923$		$\pm i \ 0.240$	$\pm i \ 0.768$		
$ \lambda_2 /\lambda_1$	0.3104	0.6731	0.412	0.2696	0.6731	0.4127	0.2571	1.	1.
	$\widehat{M_{77}}$	$\widehat{C_{12}}$	$\widehat{D_{12}}$	$\widehat{M_{24}}$	$\widehat{C_{14}}$	$\widehat{D_{15}}$	$\widehat{M_{29}}$	$\widehat{F_{24}}$	$\widehat{F_{29}}$
N. of Re EVs $\neq 0$	61	11	11	24	12	15	29	22	26
N. of $EVs = 0$	16	1	1	0	2	0	0	2	3
Largest EV	8.226	3.089	3.9285	7.2485	3.288	4.072	7.450	4.0595	4.1905
$\tilde{\lambda}_2$ if Re EV	2.771	1.1615	1.5530	1.9845	1.4895	1.8745	2.305	1.3785	1.4745
$  ilde{\lambda}_2 $	3.824 !!	2.050	1.845 !!	2.5635	2.078 !!	1.920 !!	2.748 !!	4.0595	4.1905 !!
$  ilde{\lambda}_2 /  ilde{\lambda}_1 $	0.4648	0.6636	0.4696	0.3537	0.6320	0.4715	0.3689	1.	1.
$S^*(\text{Eq.3})$	1.350	1.0359	0.8523	0.7930	1.1592	0.8495	0.7343	-	-

community i have been quoted by others of the same community i. Self-citations are disregarded,  $m_{ii} = 0$ , i.e. all diagonal terms in  $M_0$ ,  $C_0$ , and  $D_0$  are 0; see [26] for the list of all finite matrix elements. In contrast,  $F_0$ , i.e.

$$F_0 = \begin{pmatrix} 0 & A \\ B & 0 \end{pmatrix}. \tag{2}$$

emphasizes links between different communities, i.e. agents of community j quoting those of community  $i(\neq j)$ ;  $i \leftarrow j$ . A and B are obviously rectangular matrices describing inter-community links. A and B are (40x37) and (37x40) matrices respectively. All  $C_0$ , A, B and  $D_0$  matrices are given in the Appendix; from such matrices, the network, not shown for space saving, can be easily reconstructed through any good classical graph software.

Moreover, since each square matrix  $M_0$ ,  $C_0$ ,  $D_0$ ,  $F_0$  has non-negative elements, the Perron-Frobenius theorem states that there exists at least one non-negative eigenvalue greater or equal in absolute value than all other eigenvalues; its corresponding eigenvector has non-negative components [27, 28].

The Perron-Frobenius theorem, applied in its version for non-negative matrices only, indicates that there may exist eigenvalues of the same absolute value as the maximal one.

The EVs of the above 4 matrices,  $M_0$ ,  $C_0$ ,  $D_0$ , and  $F_0$ , have been computed. The EVs of interest are given in Table 2. In the framework of this paper only these relevant EVs are indicated.

#### 2.4 Reduced size "core networks"

To proceed on knowledge diffusion on a network, it should be recognized that some knowledge is lost when the agent is not well connected, i.e. has a node degree = 1, either being at the end of a "dangling bond", - like a sink or a source in fluid mechanics. The same can be thought for a node degree = 2. The role of these agents is likely marginal in contrast to those sinks and sources which are hubs of the network. In fact for the diffusion of knowledge, a triad graph seems the most basic graph to consider. Thus, for the present study, a few nodes of the whole network can be eliminated from the start.

The following procedure has been applied: in order to emphasize the role of inter-community connecting agents, all agents in the A and B rectangular matrices are kept when  $a_{i,j} = 1$  and  $b_{i,j} = 1$ , whence reducing the entire community network to its relevant core according to inter-community links. Next, the most important agents in the C and D matrices are conserved as nodes relevant for intra-community knowledge transfer. Remembering that an odd or an even number of nodes might lead to different sets of (real or complex) eigenvalues, it is interesting to compare two related networks different by only one node unit. It results that the following cases are be considered:

- a network made of 12 ISP
- a network made of 12 DED
- a network made of 24 nodes: 12 DED and 12 IDP
- a network made of 14 IDP
- a network made of 15 DED
- a network made of 29 nodes: 14 IDP and 15 DED

Each network is represented by its adjacency matrix:  $C_{12}$ ,  $D_{12}$ ,  $M_{24}$ ,  $C_{14}$ ,  $D_{15}$ , and  $M_{29}$ . Moreover, in order to investigate further any effect in the inter community "knowledge sharing", the corresponding F matrices, i.e.  $F_{24}$  and  $F_{29}$  have to be specifically used. Recall that none of these 8 matrices are symmetric.

#### 2.5 Aggregation matrix (or network) construction

The above networks, reproducing citations, contain some directed links (and UL as well). For each considered ("time-dependent") network, an "aggregated network" can be defined though a (new) adjacency matrix, e.g.  $M_{i,j} \to \widehat{M_{i,j}}$ , etc., - for the 8 cases outlined here above. These new 8  $\widehat{M_{i,j}}$  matrices are necessarily symmetric.

#### 3 Results

For each (16) matrix, the eigenvalues (and eigenvectors) have been calculated. The main characteristic results relevant to the present investigation are given

in Table 2. To distinguish between the number of real EVs  $\neq 0$  or 0 is not the presently relevant subject. However, it is at once pointed out that the largest EV is of course real and positive in each case, but the magnitude of the most negative EV might be larger than the "Next to Largest" Re (positive) EV, a fortiori if the latter is negative. Thus, in Table 2, and in view of preparing the following sections and discussion, both the strictly "Next to Largest" Re (positive) EV is given but also the EV having the "Next to Largest Modulus". It can be seen from this Table that the networks containing DED are those for which the distinction on the notion of "next to largest" EV is relevant.

### 4 Slow-down or Speed-up knowledge diffusion

It has been shown that changes of diffusion dynamics in temporal networks as compared to their static counterparts are due to the change of connectedness or conductance of the corresponding second-order aggregate network. These changes influence the process of knowledge diffusion through a slow-down or speed-up factor which can be computed based on the second-order aggregate networks corresponding to a particular non-Markovian temporal network and its Markovian counterpart. This basically consists in comparing two corresponding adjacency matrix features. In the present case, where the usual temporal aspects is masked but replaced by a sequential one (of quotations), the matter consists in comparing the original adjacency matrix and its symmetrized counterpart.

It was interestingly shown that the convergence time of random walks is related to the second largest eigenvalue of the transition matrix T. For a primitive stochastic matrix with (not necessarily real) eigenvalues  $1 = \lambda_1 > |\lambda_2| > |\lambda_3| \ge \cdots \ge |\lambda_n|$ , it was shown that the number of steps k after which the total variation distance  $\Delta(\pi_k; \pi)$  between the visitation probabilities  $\pi_k$  and the stationary distribution  $\pi$  of a random walk falls below  $\epsilon$  is proportional to  $1/\ln(|\lambda_2|)$ . For a matrix  $T^{(2)}$  capturing the statistics of two-paths in an empirical temporal network and a matrix  $\tilde{T}^{(2)}$  representing the Markovian model derived from the symmetrized network, an analytical prediction for the change of convergence speed  $S^*$ , due to non-Markovian properties can be derived as

$$S^*(T^{(2)}) := ln(|\tilde{\lambda}_2|)/ln(|\lambda_2|) \tag{3}$$

where  $\lambda_2$  and  $\tilde{\lambda}_2$  denote the second largest eigenvalue of  $T^{(2)}$  and  $\tilde{T}^{(2)}$  respectively. Thus, a diffusion slow-down exists if  $S^*(T^{(2)}) \geq 1$ . A diffusion speed-up exists if  $S^*(T^{(2)}) \leq 1$ . To calculate  $S^*(T^{(2)})$ , in the present cases, observe that Eq. (3) must be adapted to take into account the ("normalizing")  $\lambda_1$  value; see ad hoc line in Table 2.

In the present network cases, a temporal network adjacency matrix can have its "second largest eigenvalue", i.e. to be considered as the "next to largest" eigenvalue, either real (positive or negative, in fact) or be a c.c. eigenvalue with a large modulus.

The relevant results are given in Table 2 last line. For a global view of the data, one can rank the  $S^*(T^{(2)})$  values in decreasing order: this corresponds to

rank the networks as follows:  $M_{77}$ ,  $C_{14}$ ,  $C_{12}$ , which have a slow-down feature, while  $D_{12}$ ,  $D_{15}$ ,  $M_{24}$ , and  $M_{29}$  possess a speed-up feature.

It is deduced that

- (i) the diffusion of knowledge is more difficult on the large (complete) network, but this could have been expected;
- (ii) the same type of hierarchy constraint on the network size is found either for the slowing-down or speeding up processes;
- (iii) however, the IDP and DED sub-networks are markedly different: the diffusion of knowledge is slower for IDP, but faster for DED; this (a priori unexpected finding) might nevertheless be "rationalized", if one attempts to introduce some "level of scientific quality" in the behavior of the various agents. This perspective offers some opening discussion toward tying psychology, intellect, scientific knowledge to belief. However, one cannot completely neglect the fact that the DED might have more use in publishing thoughts than IDP, who might be less prone to practically publish, whence be quoted;
- (iv) another interesting point pertains to the relative influence of the agents on the (reduced, but pertinent) networks: the diffusion of knowledge is markedly in favor of the DED, since the  $M_{24}$  and  $M_{29}$  corresponding speeds are obviously on the up side.

#### 5 Conclusion

As a conclusion, let a brief summary be given tying the "questions" to the "answers". In the main text, it has been studied whether the diffusion of knowledge can be measured in and outside distinct communities, necessarily made of stubborn agents on small world-like networks. This speed of knowledge diffusion is obtained from the eigenvalues of the corresponding adjacency matrices for the whole set of agents and for their sub-communities. In particular, it has been found that the Neocreationist and Intelligent Design Proponents (IDP), on one hand, and the Darwinian Evolution Defenders (DED), on the other hand behave quite differently in processing the knowledge. A quantification of the slow-down or speed-up effects of information diffusion in such temporal networks, with non-Markovian contact sequences, has been made. It is observed that the diffusion of knowledge is slower in IDP and faster in DED communities. It is argued that the finding can be "rationalized", if some "scientific quality" and "publication habit" are attributed to the agents, as common sense would suggest. This finding offers some opening discussion toward tying scientific knowledge to belief, and subsequent diffusion of both in small worlds.

Moreover, a brief observation has been made on the community size effect, and its substructure. It is observed that the diffusion of knowledge is more difficult on large networks. It is also observed that the number of triads with heterogeneous agents seems a relevant "parameter". In the present cases, a

speed-up process effect is markedly greater when two DED agents are involved, whence again likely pointing to some behavior origin in the more usual scientific arguing methods prone to such a community. Since it has been found in [16] that the origin of complex eigenvalues is related to the structure of triads, further work on the relationship between the (density of) different types of triads and the speed of knowledge diffusion should be interesting.

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# Appendix IDP-DED matrix

In this Appendix, the adjacency matrices of interest,  $C_0$ , A, B,  $D_0$ , are recalled.

$C_0$	1 · · ·			37
1	011100000	1011111000	0 1 0 1 0 0 0 0 0 1	0 1 0 0 0 0 1 0
2	$1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0$	$0\; 0\; 1\; 1\; 1\; 1\; 1\; 0\; 0\; 0$	0 1 0 1 0 0 0 0 0 1	0 1 1 0 0 0 1 0
3	100000010	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0$	1100000010	0 0 0 0 0 0 0 0
4	$1\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1$	$1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0
5	101101011	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0010000000	0 0 0 0 0 0 0 0
6	$1\ 0\ 1\ 0\ 0\ 0\ 0\ 1\ 0$	0 0 0 0 0 0 0 0 0 0	0 0 0 1 0 0 0 0 0 0	0 0 0 0 0 0 0 0
7	$1\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0$	0 0 0 0 1 1 1 0 0 0	0 0 0 0 0 0 0 0
8	$0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 1$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 1 1 1	$1\ 1\ 0\ 0\ 0\ 0\ 0\ 0$
9	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 0 0	0 0 1 1 0 0 0 0
10	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 1 0	0 0 1 0 1 1 0 0
11	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0$	0 0 0 0 0 0 0 0 0 0	0 1 0 0 0 0 1 1
12	0 0 0 0 0 0 0 0 0	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
13	0 0 1 0 0 0 0 0 0	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0
14	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
15	$1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
16	$1\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
17	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0 0 0 0 0 0 0 0
18	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$  0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 $	0 0 0 0 0 0 0 0
19	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
20	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 1 0	00000000000	0 0 0 0 0 0 0 0
21	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
22	0 1 0 1 0 0 0 1 1	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 1 1 1	11000000
23	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	00000000000	0 0 0 0 0 0 0 0
24	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	00000000000	0 0 0 0 0 0 0 0
25	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	00000000000	0 0 0 0 0 0 0 0
26	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
27	0 0 0 0 0 0 0 0 1	0 0 0 0 0 1 0 0 0 0	0 0 0 0 0 0 0 0 1 0	0 0 0 0 0 0 0 0
28	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
29	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
30	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	00000000
31	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 1 0	0 0 0 0 0 0 0 0
32	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
33	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
34	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
35	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 1 0 0 0 0 0 0	0 0 0 0 0 0 0 0
36	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
37	0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0

Table 3: Matrix  $C_0$ 

$D_0$	38 · · · 43 · · · 47	48 53 57	$58 \cdots 63 \cdots 67$	68 73 77
38	0111001101	0000000000	0001000001	0110000010
39	1010000100	00000000000	00000000000	0100000000
40	1101001100	00000000000	0001000000	0000000001
41	0000010000	00000000000	0000000000	0000000001
42	0001010000	00000000000	0000000001	0000000001
43	1001000000	0000000000	0010000000	0000000000
44	0001001000	0010000000	0000000000	100000011
45	1000000000	0000000001	0100000000	0000001010
46	1001000000	0000000000	00000000000	0000000000
47	0010000000	0000000000	00000000000	0000000000
48	0000000001	0000000000	00000000000	0000000000
49	00000000000	0000000000	00000000000	0000000000
50	1000000001	00000000000	0 0 0 1 0 0 1 0 0 0	0000000010
51	0 0 0 0 0 0 0 0 0 0	00000000000	0 0 0 1 0 0 0 0 0 0	0000000000
52	00000000000	00000000000	0 0 0 0 0 0 0 0 0 0	0000000000
53	0010000100	$0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1$	0 0 0 0 0 0 0 0 0 0	0000000010
54	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	0000000000
55	00000000000	00000000000	00000000000	0000000000
56	0000000000	0000000000	0000000000	0000000000
57	00000000000	0000000000	0000000000	0000000000
58	00000000000	00000000000	0000000000	0000000000
59	00000000000	00000000000	0000000000	0000000000
60	10000000000	0000000000	0000000000	0000000000
61	0000000000	0000000000	0000000000	0000000000
62	0000000000	0000000000	0000000000	0000000000
63	0000000000	0000000000	0000000000	0000000000
64	0000000000	0000000000	0000000000	0000000000
65	100000100	0000010000	010000010	0000000000
66	0000000000	0000000000	0 0 0 0 0 0 0 0 0 0 0	0000000000
67	0000000000	0000000000	0000000000	0000000000
68	0000000000	0000000000	0000000000	0000000000
69	0000000000	0000000000	0000000000	0000000000
70	0000000000	0000000000	0000000000	0000000000
71	0000000000	0000000000	0000000000	0 0 0 0. 0 0 0 0 1 0
72	0000000000	0000000000	0000000000	0000000000
73	0000000000	0000000000	0000000000	0000000000
74	0000000000	0000000000	0000000000	0 0 0 0 0 0 0 0 1 0
75	0000000000	0000000000	0000000000	0000000000
76	1100001100	0010001000	0000000000	0 0 0 0 0 0 0 0 0 0 0
77	0001000000	00000000000	00000000000	0 0 0 0 0 0 0 0 0 0 0.

Table 4: Matrix D

A	38 ··· 43 ··· 47	48 53 57	58 63 67	68 73 77
1	1111111100	0000110010	00001010101	100000011
2	1111101111	0111010000	$0\ 1\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 1$	1001000011
3	1011001100	0000111111	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	000000010
4	0 0 1 1 0 0 0 0 0 0	00000000000	$1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0000000000
5	$1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0$	0000000000	0100000000	0000000000
6	0 0 0 0 0 0 0 0 1 0	0001000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0000000000
7	$1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0$	0001000000	$0\ 0\ 0\ 1\ 1\ 1\ 0\ 0\ 0\ 0$	0000010000
8	0 0 1 0 0 0 0 0 0 0	0000000000	0100000000	0000000000
9	0 0 0 0 0 0 0 1 0 0	0000000000	$0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0$	0000000000
10	$1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	0000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 0$	0000001100
11	0 0 0 1 0 0 0 1 0 0	0010000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	100000010
12	0 0 0 0 0 0 0 0 0 0	0000000000	00000000000	0000000000
13	0 0 0 0 0 0 0 0 0 0	0000000000	00000000000	0000000000
14	0 0 0 0 0 0 0 0 0 0	0000000000	0 0 0 0 0 0 0 0 0 0	0000000000
15	0010000000	0000000000	00000000000	0000000000
16	0010000000	0000000000	00000000000	0000000000
17	0 0 0 0 0 0 0 0 0 0	0000000000	00000000000	0000000000
18	00000000000	0000000000	00000000000	0000000000
19	00000000000	0000000000	00000000000	0000000000
20	0 0 1 0 0 0 1 0 0 0	0000000000	00000000000	0000000000
21	00000000000	0000000000	00000000000	0000000000
22	0010000000	0000000000	0100000000	0000000000
23	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
24	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
25	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
26	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
27	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000001
28	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
29	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
30	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
31	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
32	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
33	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
34	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000000
35	0 0 0 0 0 0 0 0 0 0	00000000000	00000000000	00000000000
36	0 0 0 0 0 0 0 0 0 0	00000000000	00000000000	00000000000
37	0 0 0 0 0 0 0 0 0 0	00000000000	0 0 0 0 0 0 0 0 0 0	00000000000

Table 5: Matrix A

B	1 5 9	10 15 19	20 · · · 25 · · · 29	30 37
38	110000000	0000000000	0000000010	00000010
39	110000000	0000001000	0000001010	00001000
40	100000000	00000000000	00000000000	00001000
41	100000000	0000000000	00000000000	00000000
42	100000000	0000000000	00000000000	00001000
43	000000000	0000000000	0000000000	00000000
44	001000000	0000000000	00000000000	00000000
45	110000000	0010000000	$0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0$	00001000
46	100000000	0000000000	00000000000	00000000
47	000000000	00000000000	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000
48	000000000	00000000000	00000000000	00000000
49	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	$0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$	00000000
50	000000000	00000000000	0 0 0 0 0 0 0 0 0 0	00000000
51	010000000	0000000000	00000000000	00000000
52	000000000	0000000000	0 0 0 0 0 0 0 0 0 0	0 0 0 0 0 0 0 0
53	001000000	00000000000	0 0 0 0 0 0 0 0 0 0	00000000
54	000000000	00000000000	00000000000	0 0 0 0 0 0 0 0
55	000000000	00000000000	0 0 0 0 0 0 0 0 0 0	00000000
56	000000000	0000000000	0000000000	00000000
57	000000000	0000000000	0 0 0 0 0 0 0 0 0 0	00000000
58	000000000	0000000000	0 0 0 0 0 0 0 0 0 0	00000000
59	000000000	00000000000	00000000000	00000000
60	000000000	0000000000	0000000000	00000000
61	000000000	0000000000	0000000000	0000000
62	000000000	0000000000	0000000000	0000000
63	000000000	0000000000	0000000000	0000000
64	000000000	0000000000	0000000000	00000000
65	000000000	0000000000	000000010	0000000
66	000000000	0000000000	0000000000	0 0 0 0 0 0 0 0
67	000000000	0000000000	0000000000	0000000
68	000000000	0000000000	0000000000	0 0 0 0 0 0 0 0
69	000000000	0000000000	0000000000	0000000
70	00000000	0000000000	0000000000	0000000
71	000000000	0000000000	0000000000	0000000
72	000000000	0000000000	0000000000	0 0 0 0 1 0 0 0
73	000000000	0000000000	0000000000	0000000
74	000000000	0000000000	0000000000	0 0 0 0 0 0 0 0
75	000000000	0000000000	0000000000	0000000
76	111001110	000000000000	0000000000	0 0 0 0 0 0 0 0
77	000000000	00000000000	00000000000	00000000

Table 6: Matrix B

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